

Article

Land and Forest Degradation inside Protected Areas in Latin America

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Received: 8 August 2013; in revised form: 15 October 2013 / Accepted: 5 November 2013 /

Published: 13 November 2013

Abstract: Using six years of remote sensing data, we estimated land and forest degradation inside 1788 protected areas across 19 countries in Latin America. From 2004–2009, the rate of land and forest degradation increased by 250% inside the protected areas, and the land and forest degradation totaled 1,097,618 hectares. Of the protected areas in our dataset, 45% had land and forest degradation. There were relatively large variations by major habitat type, with flooded grasslands/savannas and moist broadleaf forest protected areas having the highest rates of degradation. We found no association between a country's rate of land and forest degradation inside protected areas and Gross Domestic Product (GDP) per capita, GDP growth, or rural population density. We found significant, but weak, associations between the rate of land and forest degradation inside protected areas and a country's protected area system funding, the size of the protected area, and one International Union for the Conservation of Nature (IUCN) management category. Our results suggest a high degree of heterogeneity in the variables impacting land and forest degradation inside protected areas in Latin America, but that the targeting of protected area investments on a continental scale is plausible.

Keywords: habitat conversion; deforestation; effectiveness; Terra-i; Normalized Differential Vegetation Index (NDVI); remote sensing; South America; Central America

1. Introduction

From 1990 to 2010, the coverage of terrestrial protected areas increased from 8.8% of global land area to 12.7% [1]. Much of the growth in protected area coverage was in South and Central America (“Latin America” henceforth). In 1990, the average country in Latin America had 11.6% of territorial area within formally designated terrestrial protected areas. Two decades later, the average country had 19.3% [1]. In Latin America, 15 out of 20 countries have more than 10% of their terrestrial area protected, and 7 countries have more than 25% protected [1]. Latin America now has a higher percentage of terrestrial areas formally protected than any other region of the world [2].

Are protected areas in Latin America effective? If we use the International Union for the Conservation of Nature (IUCN) definition of a protected area as “a clearly defined geographical space, recognized, dedicated and managed, through legal or other effective means, to achieve the long-term conservation of nature with associated ecosystem services and cultural values” [3], then the primary question regarding effectiveness is: are Latin American protected areas achieving the “long-term conservation of nature”?

There have been a number of protected area effectiveness assessments, including studies on protected area management [4,5], conserving species diversity [6], coverage of global biomes and habitats [7], reducing deforestation [8], and maintaining populations of large mammals [9]. While there are multiple means of assessing protected area effectiveness, one crosscutting indicator of protected area effectiveness is land-cover change, specifically conversion of natural habitat to human-influenced habitat. Land cover frequently correlates with species-specific habitat [10], carbon sequestration [11], and habitat connectivity or fragmentation [12]. Preventing anthropogenic land-cover change could be viewed as central to protected areas’ goal of the long-term conservation of nature.

If preventing land-cover changes is a core element for protected areas’ long-term conservation of nature, then one measure of protected areas’ effectiveness could be the rate of short-term land and forest degradation. We posit that this is a reasonable metric for protected area effectiveness, and one that is comparatively straightforward to quantify at a large scale via remote sensing. Granted, not all land and forest degradation observed by remote sensing is anthropogenic (e.g., landslides and lightning fires), but it is a reasonable assumption that the majority of year-on-year land and forest degradation is anthropogenic.

There have been several global studies [13,14] and a number of localized studies, e.g., [15–17] of land and forest degradation in protected areas, but large datasets at a continental scale have yet to be analyzed. The availability of time-series moderate resolution remote sensing imagery and the growing sophistication of imagery analysis give the potential to track land and forest degradation within a large number of protected areas with a high degree of precision.

Here we look at protected areas throughout Latin America and use remote-sensing land-cover data to answer the research question: how are changes in land and forest degradation within protected areas in

Latin America related to Gross Domestic Product (GDP) per capita, GDP growth, rural population density, protected area system funding, habitat type, IUCN management category, and protected area size?

We improve upon existing protected area effectiveness assessments in three ways. First, we conduct a continent-scale assessment with a large sample size relative to other assessments. Second, we use six years of biweekly remote sensing data to measure changes, giving the results a higher degree of precision than previous assessments. Third, we analyze a relatively large number of variables potentially associated with land and forest degradation inside protected areas.

2. Methods

To detect land and forest degradation, we use a Terra-i dataset comprised of 16-day blocks of Moderate Resolution Imaging Spectroradiometer (MODIS) data with a resolution of $250\text{ m} \times 250\text{ m}$ per pixel (6.25 hectares). The validity and reliability of the MODIS data to detect land and forest degradation has been tested in multiple studies, e.g., [18–20], and MODIS remote sensing imagery has been successfully used to detect land and forest degradation in the tropics since 2004 by the DETER system at Brazil's National Institute for Space Research [21] and since 2000 by the Indonesia FORMA project at the Center for Global Development [22]. The Terra-i dataset identifies changes in land cover with an algorithm based on a multilayer perception neural network and Bayesian theory to identify changes in time-series Normalized Differential Vegetation Index (NDVI) data [23].

Changes in NDVI can have positive or negative values. NDVI has been shown to reliably detect negative changes, such as deforestation and land degradation, in diverse contexts and habitats, e.g., [24,25], but methodologies for interpreting positive changes have yet to be rigorously validated. Hence, we use only the negative values in measuring land-cover change.

One of the main difficulties of land and forest degradation detection from remote sensing is accounting for the “noise” from the scattering and absorption of the signal as it passes through the atmosphere [26]. Terra-i uses the Harmonic Analysis of NDVI Time Series (HANTS) algorithm to remove atmospheric noise by smoothing the NDVI curve and inferring the value of missing data [27].

Floods and droughts may cause anomalous changes in NDVI data [28]. Floods tend to generate large shifts in vegetation indices [28–30] while droughts can lead to a slight reduction in NDVI values. Terra-i uses the MODIS MOD35 product [31] to mask pixels where water has been detected and that have potentially been flooded and uses the Tropical Rainfall Measuring Mission data [32] to detect anomalies within the precipitation data and flag droughts. The first year for the Terra-i land-cover data was 2004, and we use a 2004–2009 Terra-i dataset (six years).

The World Database on Protected Areas (WDPA) provided 2551 terrestrial protected areas in Latin America with data on location and area that were established prior to 2004 [1]. We excluded 109 protected areas with less than 50% remote sensing data coverage due to frequent high-density cloud cover. We further excluded 646 protected areas that were smaller than 500 hectares because one pixel equals 1.25% of 500 hectares, and a change in a single pixel results in a relatively large percentage change in land cover. We also excluded as outliers eight protected areas due to the sensitivity of the statistical model to outliers. Our final dataset has 1788 protected areas across 19 Latin American countries (Table 1).

Table 1. Country and number of protected areas included in the analysis.

Country	Number of protected areas
Argentina	166
Belize	43
Bolivia	74
Brazil	563
Chile	68
Colombia	38
Costa Rica	15
Ecuador	25
El Salvador	29
French Guiana	10
Guatemala	99
Guyana	1
Honduras	74
Mexico	341
Nicaragua	39
Paraguay	27
Peru	56
Suriname	12
Venezuela	108
Total	1788

There are risks of biases in our sample of protected areas. If the 109 protected areas we excluded due to limited remote sensing data were subject to less anthropomorphic land and forest degradation because of shrouding by clouds or high precipitation, then this could conceivably bias the results towards an overestimation of the land and forest degradation rate of change. If the 646 protected areas we excluded due to small size were subject to greater land and forest degradation because of higher perimeter-to-interior-area ratios, then this could conceivably bias the results towards an underestimation of the land and forest degradation rate of change.

For the comparisons by major habitat types, we use WWF's terrestrial biomes to define habitat type and spatial extent [33]. For the comparisons by country, we use GDP per capita, GDP growth, and rural population density from the World Bank's World Development Indicators [34] along with protected area funding levels from Bovarnick *et al.* [35]. For the analysis by IUCN protected area management category [3], we use the categories in the WDPA database [1].

We include an analysis of land and forest degradation inside protected areas and in 5-km and 20-km wide zones surrounding the protected areas. Such comparison of land and forest degradation inside protected areas with land and forest degradation in adjacent areas can exaggerate the protection effectiveness if protected areas are more isolated than their adjacent areas [14]. Comparing protected area and adjacent area land and forest degradation has also been shown to overestimate the effectiveness of protected areas due to different conditions in the buffer zones [36,37]. Thus, our inclusion of an inside-outside comparison should not be viewed as evidence for or against protected areas as effective tools for reducing land and forest degradation compared to adjacent areas. Our aim is simply to show land and forest degradation trends at the continental scale.

For the data analysis, we use a random-effects tobit model with a panel-data structure. The dependent variable (land and forest degradation) is characterized by many observations at zero. Using ordinary least-square analysis with this dependent variable would lead to biased parameter estimates [38]. As the zeros in this dataset can be interpreted as “too small to measure”, we are dealing with left-censored, continuous data. The tobit model was developed to analyze censored data and allows the simultaneous estimation of the influence of explanatory variables on the probability of the limit responses (*i.e.*, the zeros or “no change” observations in our data) and the size of non-limit responses (*i.e.*, the non-zeros: the observations with land and forest degradation) [39]. As our data are clustered by country, we opted to use a panel-data structure to control for correlation between protected areas from the same country. The use of tobit regression with random effects allows for an appropriate analysis of such data and avoids bias in the estimates, which is a common problem in fixed-effects tobit models [40]. In addition to the tobit model, we also use the Wilcoxon matched-pair signed-rank test [41] and Friedman’s two-way ANOVA by ranks test [42,43] to assess statistical differences between the protected and the adjacent zones, and between different years, respectively. These non-parametric tests were selected due to the lack of normality in the distribution of the land and forest degradation data. The analyses were performed using statistical packages Stata 10 (command `xttobit`) and SPSS 21.

3. Results and Discussion

In Latin America, the rate of land and forest degradation inside protected areas more than doubled from 2004 to 2009, increasing from 0.04% to 0.10% per year. This is a small fraction but of a large number. Thus, in 2004 there were 81,975 hectares of land and forest degradation inside protected areas in Latin America, while in 2009, there were 247,056 hectares—an increase of approximately 165,000 hectares. Assuming each land and forest degradation event was unique (*i.e.*, no change, regrowth and change again during the six years) and considering only the negative changes in land cover, the 2004–2009 land and forest degradation in our protected area dataset was 1,097,618 hectares—an area the size of Jamaica.

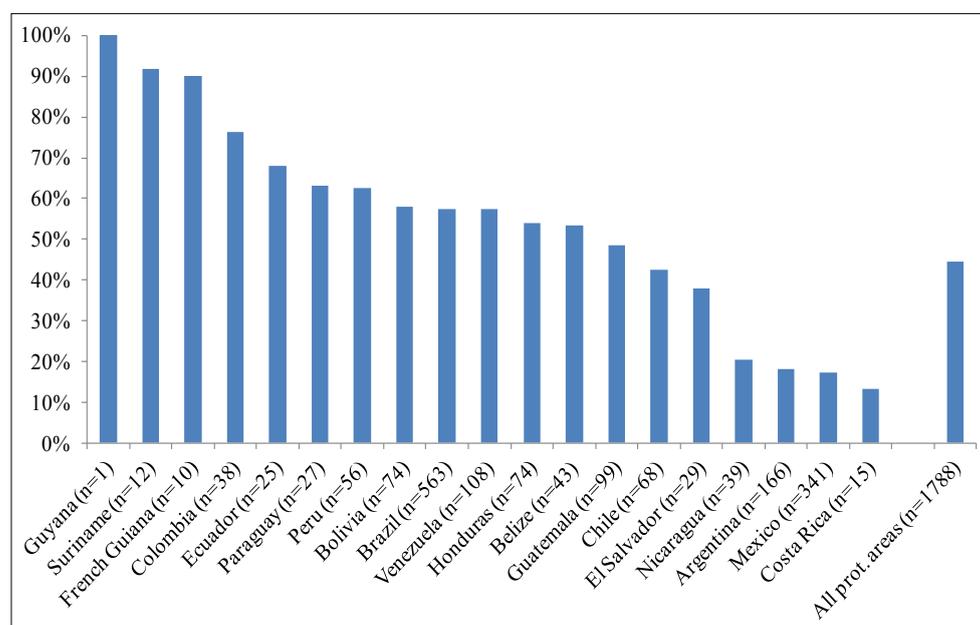
3.1. Differences by Country

The mean annual rate of land and forest degradation 2004–2009 shows large differences by country, with French Guiana and Guatemala at more than double the Latin American average and Nicaragua and Mexico at less than one-fifth the average (Table 2).

Guyana, Suriname and French Guiana are the countries where the percentage of protected areas with observed land and forest degradation is highest, but all three have small sample sizes (Figure 1). Guatemala and Brazil have relatively high rates of land and forest degradation (Table 2), yet fall to the middle in Figure 1, indicating that the high rates of land and forest degradation are caused by relatively large changes in relatively few protected areas. On the other hand, Peru’s protected areas have experienced low average change but that change occurred in over 60% of its protected areas. Overall, 45% of all protected areas experienced land and forest degradation inside their administrative boundaries from 2004 to 2009.

Table 2. 2004–2009 mean annual change in land and forest degradation inside protected areas by country (standard deviations in parentheses).

Country	Number of protected areas	Mean annual change in %		Mean annual change in hectares	
French Guiana	10	0.231	(0.465)	51	(54)
Guatemala	99	0.206	(0.390)	228	(1003)
Paraguay	27	0.183	(0.391)	71	(285)
El Salvador	29	0.132	(0.288)	3	(8)
Brazil	563	0.127	(0.353)	156	(717)
Bolivia	74	0.104	(0.214)	443	(1010)
Colombia	38	0.086	(0.118)	214	(357)
Ecuador	25	0.076	(0.132)	82	(202)
Honduras	74	0.067	(0.163)	72	(289)
Belize	43	0.054	(0.101)	9	(21)
Suriname	12	0.046	(0.099)	17	(23)
Argentina	166	0.044	(0.184)	13	(110)
Chile	68	0.039	(0.095)	15	(34)
Venezuela	108	0.028	(0.072)	107	(325)
Costa Rica	15	0.016	(0.043)	1	(5)
Guyana	1	0.015	(n/a)	69	(n/a)
Peru	56	0.014	(0.023)	79	(297)
Nicaragua	39	0.013	(0.041)	5	(23)
Mexico	341	0.013	(0.071)	4	(22)
All protected areas	1788	0.080	(0.253)	102	(536)

Figure 1. 2004–2009 proportion of protected areas with land and forest degradation by country.

Other authors have suggested that income level and rural population density could be explanatory factors for variations in protected area land and forest degradation within a country [13,44]. We expand this and look at whether GDP per capita (as a proxy for income level), GDP growth

(as a proxy for economic expansion), and average rural population density for a country (as a proxy for population densities around protected areas) can explain the differences between countries in land and forest degradation within protected areas. We acknowledge that GDP is an imprecise measure of income and economic expansion due to underlying issues with national accounts data [45] and that there can be large variations in rural population densities within a country [37], but we hypothesize that these may be explanatory factors for the observed country-level variation in protected area land and forest degradation.

Another possible explanatory factor is differing levels of protected area system funding. To test this hypothesis, we use Bovarnick *et al.*'s data on 2007–2008 protected area system spending from all known sources for 12 Latin American countries (as a proxy for protected area system funding) [35].

Using a panel-data tobit regression model with random effects, we tested for an association between the average annual rate of land and forest degradation between 2004–2009 inside protected areas and the independent variables of GDP per capita, GDP growth, rural population density, and protected area system funding. Data on protected area system funding were unavailable for Belize, Costa Rica, El Salvador, French Guiana, Guyana, Mexico, and Suriname, and thus they were excluded from the regression model.

Before running the analysis, we tested for collinearity among the independent variables. There are a number of statistically significant correlations between the independent variables, but all correlation coefficients are below 0.7 [46]. The model thus includes all four independent variables. Tobit model coefficients are not interpretable as effect sizes [47], and interpretation of coefficients should focus on the positive or negative sign of the coefficient and whether or not it is statistically significant. Our results show that among the four independent variables, only protected area funding has a statistically significant relationship with land and forest degradation inside protected areas (Table 3). Our finding, however, of an association between protected area funding and land and forest degradation is tenuous and depends on the observations in just one country. Argentina's protected area system funding level was more than three times the average for the countries in the dataset (US\$8.60 *versus* US\$2.50 per hectare), while its average rate of land and forest degradation inside protected areas was roughly half the Latin America average (0.044% *versus* 0.080% per annum). If the observations from Argentina are excluded, the coefficient for protected area funding loses its significance (beta -0.047 ; SE: 0.048; $p = 0.33$; $n = 1,171$).

Table 3. Regression results for country-level independent variables.

Dependent variable: Mean land and forest degradation in %	Coefficient	Std. Error	<i>p</i> value
GDP per capita (2004)	-2.39×10^{-6}	1.64×10^{-5}	0.884
Average GDP growth (2004–2009)	-7.69×10^{-3}	2.04×10^{-2}	0.706
Average rural population density (2004–2009)	0.0026	0.0018	0.158
Funding per hectare (2007–2008)	-0.034^*	0.015	0.023
Constant	-0.027	0.18	0.817

* Significant at the 5% level or less; LL = -771.4 ; $n = 1,337$; clusters (countries) = 12; $\rho \neq 0$ indicating that the panel structure is superior to a non-panel structure.

Our finding of a non-significant relationship between GDP per capita and protected area land and forest degradation echoes Nagendra [13] who found that protected area land-cover clearing did not differ significantly among low, medium and high GDP per capita countries. This suggests that in the near term, regional growth in GDP per capita is unlikely to drive a regional change in land and forest degradation inside protected areas in Latin America.

The absence of a significant relationship between GDP growth and protected area land and forest degradation suggests that economic expansion may not be correlated with land and forest degradation inside protected areas in our dataset.

For rural population density and land and forest degradation, other authors have found that land and forest degradation in a country or region may be driven more by economic opportunities or an area's suitability for agriculture than rural population densities [48,49], and we found no statistically significant coefficient for the variable.

The tenuous association between protected area funding and land and forest degradation in our dataset could be explained by several factors. First, total spending does not necessarily reflect the spending on protection activities likely to reduce land and forest degradation such as the number of guards per square kilometers [50]. Second, spending may be concentrated in a few protected areas within a country [35].

3.2. Differences by Protected Area

As in the country-level section above, in the protected-area section below we present the descriptive statistics first and then the aggregate regression results.

3.2.1. Major Habitat Type

With protected areas categorized by major habitat type, we found that flooded grasslands and savannas had the highest mean annual change, but a single protected area in Brazil (RPPN Rosana Jubran) skews the mean annual change in percentage, and a single protected area in Bolivia (2.9-million ha San Matias) skews the mean annual change in hectares. Remove these two protected area from the analysis, and the flooded grasslands and savannas habitat type falls to third among the habitat types and tropical and subtropical moist broadleaf forest rises to the top. The latter habitat type comprises 54% of the protected areas in our dataset, and a large share of these (43%) are located in Brazil (Table 4).

The habitat type results show a split between those with large average annual changes and those with small average annual changes. There is no habitat type close to the overall average. This suggests a conservation focus in Latin America on the three habitat types with the highest rates of annual change: flooded grasslands and savannas; tropical and subtropical moist broadleaf forests; and tropical and subtropical grasslands, savannas and shrublands.

Table 4. 2004–2009 mean annual change in land and forest degradation inside protected areas by major habitat type (standard deviations in parentheses).

Major habitat type	Number of protected areas	Mean annual change in %		Mean annual change in hectares	
Flooded grasslands and savannas	15	0.146	(0.296)	367	(1208)
Tropical and subtropical moist broadleaf forests	971	0.113	(0.312)	167	(698)
Tropical and subtropical grasslands, savannas and shrublands	149	0.108	(0.270)	61	(219)
Temperate broadleaf and mixed forests	62	0.043	(0.099)	15	(33)
Mangroves	19	0.030	(0.098)	2	(6)
Tropical and subtropical dry broadleaf forests	203	0.029	(0.098)	13	(79)
Deserts and xeric shrublands	164	0.019	(0.085)	6	(31)
Temperate grasslands, savannas and shrublands	57	0.016	(0.098)	3	(15)
Montane grasslands and shrublands	51	0.015	(0.083)	22	(138)
Tropical and subtropical coniferous forests	77	0.011	(0.057)	0	(2)
Mediterranean forests, woodlands and scrub	19	0	(0)	0	(0)
Indeterminate habitat type	1	n/a		n/a	
All protected areas	1788	0.080	(0.253)	102	(536)

3.2.2. Management Categories

The WDPA dataset divides protected areas into IUCN management categories, ranging from Category I strictly protected nature reserves and wilderness areas to Category VI protected areas with sustainable use of natural resources. The management objectives of Category I-IV protected areas are more restricted than multi-use Categories V and VI protected areas.

A number of the protected areas in our dataset lack an IUCN category designation, and thus we excluded 562 protected areas with no IUCN data, including all of Mexico and El Salvador's protected areas. Category VI protected areas had the highest mean annual rate of change and Category IV had the lowest (Table 5).

Table 5. 2004–2009 mean annual change in land and forest degradation inside protected areas by IUCN category (standard deviations in parentheses).

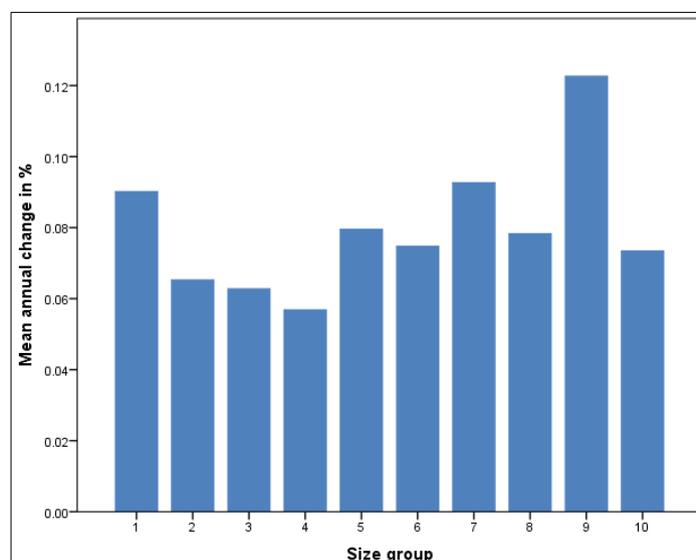
IUCN management category	Number of protected areas	Mean annual change in %		Mean annual change in hectares	
Category VI	363	0.125	(0.286)	179	(681)
Category III	60	0.091	(0.263)	84	(311)
Category I	148	0.084	(0.249)	174	(692)
Category V	83	0.075	(0.217)	31	(143)
Category II	403	0.074	(0.260)	86	(301)
Category IV	169	0.052	(0.180)	43	(365)
No specified category	562	n/a		n/a	
All protected areas	1788	0.080	(0.253)	102	(536)

IUCN management categories reflect differing management objectives rather than inherently different levels of protection against land and forest degradation, and the ambiguous results above are no surprise given that a well-managed Category V or VI protected area may be more effective in preventing land and forest degradation than a poorly managed Category I or II protected area.

3.2.3. Size

Other authors have shown that smaller protected areas with a high perimeter-to-interior-area ratio may be more prone to anthropogenic-induced changes, e.g., [51,52]. Larger protected areas may also have lower proportional land and forest degradation because they have more area that is farther away from human settlements. To facilitate the presentation of the size analysis, we split size into 10 equal groupings of $n = 178$ ranging from the smallest (size group 1) to the largest (size group 10) [53]. The larger protected areas (size groups 6–10) have a higher rate of land and forest degradation on average than the smaller protected areas (size groups 1–5) (Figure 2).

Figure 2. Mean annual rate of change by protected area group size showing slightly greater average change in the five larger size groups than the five smaller size groups.



Size groups 2–4 are the lowest suggesting that small size may not be a substantial risk factor for greater land and forest degradation. There may, however, be a threshold close to 500 hectares where the rate of land and forest degradation increases, given the relatively high rate of change in the smallest group. There also appears to be a benefit to being in the largest size, but this may be due to many of the largest protected areas in Latin America being located in remote areas such as Brazil’s 3.9 million hectares Tumucumaque National Park.

3.2.4. Regression Results for Major Habitat Type, Management Category, and Size

We also analyzed the differences in WWF-defined major habitat types, IUCN-defined protected area management categories, and protected area size using a random-effects tobit regression model with a panel-data structure. The categorical variables of habitat type and management category were

entered as dummy variables, using the variable with the greatest frequency (largest n) as the base: tropical and subtropical moist broadleaf forests and Category II protected areas. Protected areas in the habitat type Mediterranean forest ($n = 19$) were excluded given that there was no land and forest degradation in any of them. As the variable “size” has a positive skew (many small protected areas and a few very large ones), a natural log transformation of size is included in the model (Table 6).

Table 6. Regression results for major habitat type, management category, and size.

Dependent variable: Mean land and forest degradation in %	Coefficient	Std. Error	p value
Category I	−0.01	0.045	0.902
Category III	0.05	0.067	0.444
Category IV	0.02	0.050	0.655
Category V	−0.03	0.062	0.631
Category VI	0.13 *	0.033	0.000
Deserts and xeric shrublands	−0.26 *	0.080	0.001
Flooded grasslands and savannas	−0.11	0.158	0.486
Mangroves	−0.24	0.145	0.099
Montane grasslands and shrublands	−0.44 *	0.098	0.000
Tropical and subtropical coniferous forests	−0.39 *	0.128	0.002
Tropical and subtropical dry broadleaf forests	−0.19 *	0.062	0.002
Tropical and subtropical grasslands, savannas and shrublands	0.01	0.044	0.754
Temperate broadleaf and mixed forests	−0.14	0.089	0.126
Temperate grasslands, savannas and shrublands	−0.34 *	0.098	0.001
Protected area size (ln)	0.04 *	0.007	0.000
Constant	−0.49	0.083	0.000

* Significant at the 5% level or less; LL = −572.6; $n = 1217$; clusters (countries) = 17; $\rho \neq 0$ indicating that the panel structure is superior to a non-panel (pooled) structure.

We found significant differences between the base and five habitat types: deserts, montane grasslands, tropical coniferous forests, tropical dry broadleaf forests, and temperate grasslands. All these habitat types experienced lower land and forest degradation than tropical moist broadleaf forests.

Some of these habitat types mainly occur in one or two countries. For example, 73% of tropical grassland protected areas are in Brazil together with 47% of flooded grasslands, and 43% of moist broadleaf forests. To check the sensitivity of our findings, we excluded observations from several countries. Excluding protected areas in Brazil from the model does not change the habitat findings. Excluding the temperate grassland protected areas in Argentina (home to 95% of the temperate grassland protected areas in the dataset) leaves only three other protected areas with this habitat type, and the coefficient of its variable becomes non-significant.

With regard to IUCN management categories, a statistically significant difference with reference Category II was only found for Category VI protected areas. Testing other combinations of IUCN categories identified no other significant differences. Running the model without Brazil’s protected areas resulted in non-significant coefficients for all the management category variables. In a model with only Brazilian protected areas ($n = 473$), the original effect was found: only Category VI

protected areas experience a statistically higher land and forest degradation. Thus, the higher land and forest degradation association with Category VI protected areas appears to be driven by Brazil.

A study by Ferraro *et al.* [54] found 10–13% higher deforestation rates in less strictly protected areas (Categories V-VI) in Costa Rica, Thailand and parts of Indonesia—though the differences in Costa Rica stem largely from the less-threatened locations of the more strictly protected areas. Nagendra [13] found no difference in land-cover clearing for less strictly protected IUCN categories *versus* more strictly protected categories from 49 protected areas across 22 countries. Our findings largely corroborate the findings of Nagendra.

For protected area size and land and forest degradation, we found a statistically significant and positive coefficient indicating that land and forest degradation is greater in larger protected areas. Looking more closely at the data, there are two opposite trends: larger protected areas are more likely to have a land and forest degradation than smaller protected areas, but smaller protected area tend to have greater rates of change than larger protected areas when there is a land and forest degradation. The overall mean rate of change shows a mixed picture in which the first trend dominates as reflected in Figure 2.

3.3. Differences Inside and Outside Protected Areas

Protected area locations are often biased towards higher elevations, steeper slopes, and greater distances to roads and cities [37]. Moreover, a protected area's habitat type can differ substantially from its adjacent geographic areas [36]. In a global estimate of land and forest degradation inside protected areas compared to adjacent control sites matched for elevation, slope, ecoregion, distances to roads and to cities, and agricultural suitability, Joppa and Pfaff [55] found that these land characteristics were different for approximately half of the protected areas and their adjacent areas

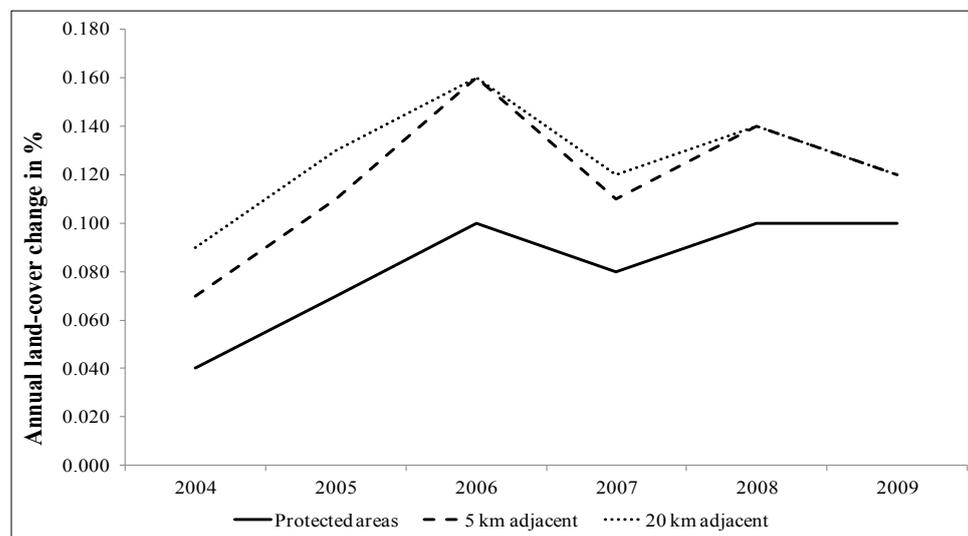
We compared the average annual land and forest degradation inside protected areas to the 5-km and 20-km wide zones adjacent to the protected areas. Both adjacent zones experienced a higher average land and forest degradation between 2004 and 2009: 0.12% and 0.13% for the 5-km and 20-km zones, respectively, *versus* 0.08% for the protected areas. Compared to the 5-km zone, land and forest degradation inside the protected areas was lower in 45% of the cases, higher in 19% of the cases, and there was no change in either area in 35% of the cases. Compared to the 20-km zone, land and forest degradation in the protected areas was lower in 66% of the cases, higher in 17% of the cases, and there was no change in either area in 17% of the cases. To test whether the differences in land and forest degradation between the protected areas and the adjacent zones are statistically significant, we used the Wilcoxon matched-pair signed-rank test, which is the non-parametric version of the paired samples t-test used for normally distributed variables. We found statistically significant differences for both the 5-km zone ($Z = 12.46$; $p < 0.001$; $n = 1787$) and the 20-km zone ($Z = 18.20$; $p < 0.001$; $n = 1787$).

This, however, should not be construed as evidence of protected areas effectively reducing land and forest degradation compared to having no protected areas. In order to be accurate, such a comparison would require matching of protected area characteristics with adjacent areas to provide the counterfactual as per Joppa and Pfaff [55] and Ferraro *et al.* [54].

Perhaps more importantly, the rate of change for all three variables increased from 2004 to 2009 (Figure 3). Using Friedman's two-way ANOVA by ranks test, which is the non-parametric version of

the repeated-measures ANOVA for normally distributed data, we find that the change over the six years are significantly different from each other at the 5% level (protected areas: $\text{Chi}^2 = 319.57$; $p < 0.001$; $\text{df} = 5$; $n = 1788$; 5-km zone: $\text{Chi}^2 = 265.63$; $p < 0.001$; $\text{df} = 5$; $n = 1787$; 20-km zone: $\text{Chi}^2 = 365.15$; $p < 0.001$; $\text{df} = 5$; $n = 1787$).

Figure 3. Mean land and forest degradation 2004–2009 for protected areas and adjacent areas showing lower change inside protected areas than in the 5-km and 20-km zones around each protected area and a general trend towards increasing land and forest degradation.



4. Conclusions

Using extensive remote sensing data, our analysis shows aggregate land and forest degradation in 1788 protected areas across 19 countries in Latin America increased 250% from 2004 to 2009. This is problematic for protected areas, which remain the primary conservation strategy in Latin America and globally [2]. Our findings suggest that protected areas in Latin America are not fulfilling their long-term goal of the conservation of nature. If protection grows in quantity and improves in quality in the next 20 years due to growing wealth and education levels as McDonald and Boucher [56] suggest, then the trend in Latin America towards increasing land and forest degradation inside protected areas could moderate.

Our results suggest a high degree of heterogeneity in the variables impacting land and forest degradation inside protected areas in Latin America. There was no statistically significant association between protected area land and forest degradation and GDP per capita, GDP growth, or rural population density, and the significance of protected area system funding depended on the inclusion of one country. We also found that the IUCN management category of a protected area has a minimal association with the *de facto* level of protection with the exception of Brazil, and that the size of the protected area has a positive and statistically significant effect on the rate of land and forest degradation. The comparison of land and forest degradation rates inside protected areas with adjacent buffer areas shows lower rates inside protected areas than outside. Moving away from the data and results, we hypothesize that agricultural expansion, grazing expansion, intentional burning, infrastructure development, and increased accessibility could all be causal factors driving protected area land and forest degradation in Latin America and are potential future areas of research.

Finally, our results suggest that a land and forest degradation trend analysis of all the terrestrial protected areas globally using remote sensing data is a possibility, and the rate of short-term land and forest degradation inside protected areas could be a viable environment indicator for the post-2015 global development goals.

Acknowledgments

We wish to thank Andy Jarvis at the International Centre for Tropical Agriculture for help with the Terra-i data, Marije Schaafsma at the University of East Anglia and Altea Lorenzo Arribas at BioSS for advice and comments on the statistical tests, and Robert Fox of the University of Maryland Graduate Program in Conservation Biology and Sustainable Development for creating the first iteration of the dataset. We would also like to thank the anonymous reviewers, especially the one who provided the detailed comments.

Conflicts of Interest

The authors declare no conflict of interest.

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